Heuristic and Metaheuristic Approaches for Green Vehicle Routing Problems with Drones

Synopsis

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1. Introduction

Drone delivery is a modern method of transporting goods from one location to another. Drones, also known as Unmanned Aerial Vehicles (UAVs) or Remotely Piloted Vehicles (RPVs), fly without a human pilot. Their advanced mobility, high speed, and flexibility make them highly desirable in several domains, such as medical, military, logistics, monitoring, disaster management, and transportation [1]. Their use is prevalent in logistics companies like FedEx, Google, and Amazon for last-mile delivery [2], [3], [4], [5].

In Military services, drones are used in combat, missile launching, spying, aerial reconnaissance, bombing, etc. They are also used as precise killing weapons. For example, drone strikes are reported during the Ukraine-Russia war [6]. In another incident, the United States used the Reaper, a precise killer drone, to kill Iranian general Qasem Soleimani just outside Baghdad airport in January 2020 [7]. Table 1 lists the applications of drones in different domains. The primary application domains are indicated in bold in the first row of the table. The corresponding references [8 – 15] broadly review the application of drones in these areas. Specific domain-wise applications are presented in each column of the table, and the associated existing solution approaches for the relevant areas are described [16-28].

Table 1: Applications of drones in various domains

Agriculture [8]	**Healthcare** [9]	**Civil** [10]	**Disaster Management** [11]**,** [12]	**Environment** [13]	**Logistics** [14]	**Military** [15]
Crop monitoring [16]	Medicine delivery [17]	Development	Search and rescue operation [18]	Air quality monitoring [19]	Last-mile Delivery [20]	Combat [21]
Soil and field analysis	Cleaning	Traffic management [22]	Disaster monitoring [23]	Underwater monitoring [24]	Supply-chain	Spying
Seed plantation	Patient first-aid [25]	Surveillance [26]		Habitat Monitoring [27]		Missile launching [28]

Drones are also popular in logistics, construction, surveying, media coverage, and agriculture. They inspect mountains, forests, and underwater areas for environmental applications. In agriculture, drones monitor crops, check water adequacy in the field, spray fertilizers, and track weeds and soil variations. In the medical delivery domain, drones deliver medical supplies such as vaccines, blood, and medicines

to remote, inaccessible locations in less time [29], [30]. During the COVID-19 pandemic, drones were also used for timely and contactless delivery of Personal Protective Equipment (PPE) kits and vaccines to doctors and health staff who were required to maintain strict quarantines and social distancing [31].

Besides the numerous advantages of drones, these devices have limitations, such as their restricted communication range, limited flight range, battery power, payload capacity, aerodynamics, and structural design [32]. The heavy payload (weight) requires high energy consumption, which is impossible with limited battery power. Therefore, proper scheduling and routing are crucial for mobility and optimal usage.

The main problems in optimizing a drone's route are trajectory optimization, path planning, and routing. Trajectory optimization focuses more on the drone's dynamic features, such as speed, angle, and altitude, to calculate energy consumption and flight range while designing the trajectory. Path planning [33], [34] is essential for drones to avoid collisions with obstacles like mountains, tall buildings, and other flying objects. The path with minimum cost and/or time is an optimal drone path. The usual delivery vehicles, generally trucks, are robust, carry heavy loads, and travel a longer distance than a drone. Therefore, the combination of trucks and drones is a new mode of delivery. The Vehicle Routing Problem (VRP) and the Traveling Salesman Problem (TSP) are the existing routing problems. However, in the context of drones give rise to new variants such as VRP with Drones (VPR-D) and Traveling Salesman Problem with Drones (TSP-D).

2. Routing Problems with Drones

The routing problems with drones are categorized into four main classes based on the types of vehicles. A combination of a drone with another vehicle (truck/electric vehicle/others) yields (a) Single Vehicle Single Drone Problems, (b) Single Vehicle Multiple Drones Problems, (c) Multiple Vehicles Multiple Drones Problems, (d) Drones Delivery Problems, as shown in Figure 1. The field of drone-assisted routing problems is receiving considerable attention, as evidenced by the large number of research publications in recent years and the wide range of related applications being developed. Several recent surveys are available in the literature on these problems.

Sabet S. et al. [35] present a survey on the green vehicle routing problems in logistics, considering several constraints, including recharging facilities, payload capacity, time windows, and drop-and-pick-

ups. The paper includes the many variants of green vehicle routing problems for fuel-based and alternative-fuel vehicles.

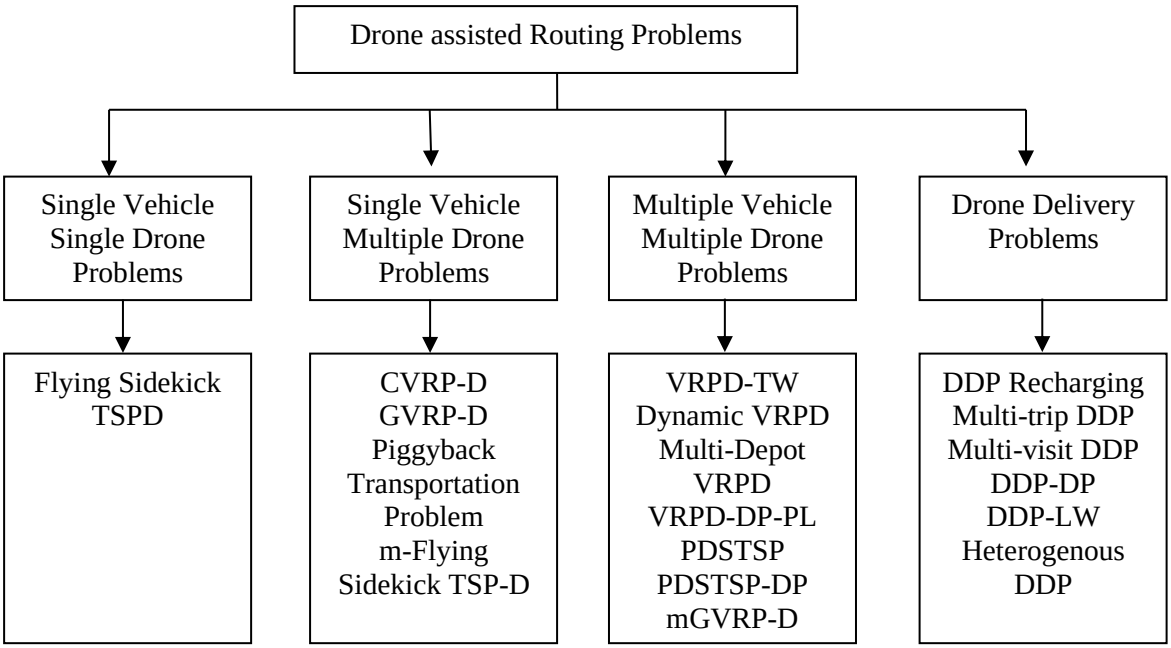

Figure 1: Classification of routing problems with drones.

Macrina G. et al. [36] study the application of drones in the context of last-mile delivery and survey various well-known drone-augmented TSP, VRP, Drone Delivery Problems (DDP), and Carrier Vehicle Routing Problems (CVRP) routing problems. Cheikhrouhou O. et al. [37] present a survey on m-TSP with current challenges in drone-aided routing. The paper explores various solution approaches, categorized into two main groups: deterministic methods and metaheuristic techniques. Otto A. et al. [10] comprehensively summarize diverse optimization approaches, emphasizing their relevance to civil applications like infrastructure, transportation, agriculture, and more. A detailed survey of VRP [38], [39] and its different variants with drones is presented in [40].

Most research papers in this field focus on a limited number of problem variants and being centered around specific application domain. However, another important aspect of the work in this area is directed towards eco-friendly routing problems, wherein conventional fuel-operated vehicles are replaced with electric vehicles. This eco-friendly approach aims to reduce carbon emissions and promote sustainable transportation solutions. The zero greenhouse gas emissions and less noise pollution make EVs environment-friendly. These vehicles act as a power source as well. The authors in [41] review existing electric vehicle routing problems with charging strategies. However, the study does not cover

electric vehicle routing problems with drones. In Section 1, the classification of drone-assisted routing problems is presented. The subsequent sections will thoroughly analyze each classification, highlighting its constraints and challenges.

2.1 Single Vehicle and Single Drone Problems

This section deals with the problem of one truck and one drone. Both vehicles start and return to the depot after making deliveries. Some deliveries are assigned to the drone, while the rest are done by truck. This problem is referred to as TSP with the drone (TSP-D). The objective of the TSP-D is to minimize the total distance/time so that all nodes are visited only once, either by drone or truck. The TSP-D optimizes the route for the service area, assuming an unlimited capacity of trucks, so they do not need to return to the depot during delivery.

TSP-D is known to be an NP-Hard (Nondeterministic Polynomial) problem, which implies that the optimal solution cannot be found in polynomial time [42]. Murray C. and Chu A. [43] introduce two different versions of TSP, the Flying Sidekick TSP (FSTSP) and the Parallel Drone Scheduling TSP (PSDTSP) depending on the synchronization between the vehicle (truck and drone).

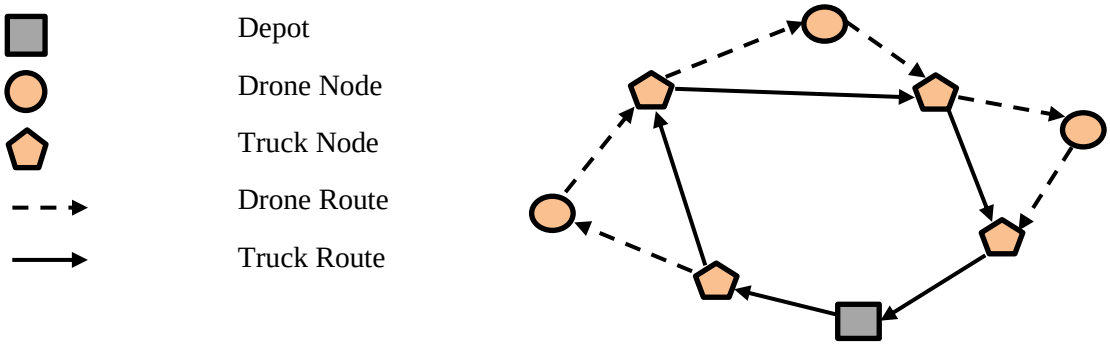

Figure 2: An example of FSTSP with a synchronized drone and truck.

In Flying Sidekick TSP (FSTSP), the truck and drone are synchronized during deliveries, and the customer must be visited once by truck or drone. Both vehicles depart and return to the depot after completing the tour simultaneously. In the meantime, the drone visits the truck back and forth for the battery replacement and to load new parcels for the next delivery. Any vehicle that reaches first must wait for the other. This results in waiting time, which must be minimum for optimality. An example of the FSTSP, where one truck and one drone are synchronized throughout the route, is given in Figure 2. A mathematical formulation is provided through MILP for one truck and one drone problem. In another

study, the authors extend the FSTSP with Multiple FSTSP (mFSTSP) for 4 heterogenous drones and 100 customer nodes [44].

Ha Q. et al. [45] propose TSP-D to minimize operational costs considering the waiting time for the vehicle. A Greedy Randomized Adaptive Search Procedure (GRASP) is utilized to find the optimal solution. The authors extend their work in another study by introducing hybrid Genetic Algorithm (GA) and dynamic programming. Dynamic population management finds the crossovers and local search operators to sift between good and bad solutions [46].

Table 2: Existing techniques for single drone and single vehicle problems

S. No.	Reference	Year	No. of Vehicles*	Problem	Approach	Objective	Problem Size
1	Poikonen S. et al. [47]	2019	1T/1D	MDRP	Branch-and-bound	Min time	Up to 200
2	Murray C. and Chu A. [43]	2015	1T/1D	FSTSP PDSTSP	MILP + Heuristics	Min time	10-20
3	Ha Q. et al. [45]	2018	1T/1D	TSP-D	GRASP	Min cost	50-100
4	Ha Q. et al. [46]	2019	1T/1D	TSP-D	HGA+ dynamic programming	Min time Min cost	16/24
5	Freitas J. et al. [48]	2020	1T/1D	FSTSP	Variable Neighbourhood Search	Min time	--
6	Dienstknecht M. et al. [49]	2022	1T/1D	TSP-DR	MIP + Dynamic Programming + GA	Min cost	400
7	Dell'Amico M. et al. [50]	2019	1T/1D	FSTSP	Branch-and-cut	Min cost	10
Vehicle* - 1T – One Truck, 1D - One Drone, 1EV – One Electric Vehicle							

A summary of the current work with one truck and one drone combination problem is shown in Table 2. The Mothership and Drone Routing Problem (MDRP) [47] is a variant of CVRP-D, with one truck and one drone. In this problem, the mother carries drones to a point, and drones serve the customers. Branch & Bound with Greedy is used to reduce the completion time. In TSP, the vehicle capacity is generally assumed to be unlimited so that the vehicle does not need to return to the depot, which is impractical. Therefore, TSP with drone resupply (TSP-DR) is introduced [49], where a drone is assigned from the depot to the truck location to refill the truck with parcels during shipment.

2.2 Single Vehicle and Multiple Drones Problems

The single vehicle and multiple drones problem is a classification of the optimization problem that involves finding the optimal route for one truck and multiple drones to visit a set of locations while minimizing travel time, energy consumption, and/or other relevant cost factors. One problem variant for one truck and multiple drones is CVRP-D, where the truck works as a carrier vehicle or mother truck for drones [51], [52]. It is a classic optimization problem that seeks to determine the optimal routing for a fleet of drones with a carrier vehicle to service a set of customers while minimizing the total distance traveled. The objective is to minimize transportation's total cost/time/energy while satisfying certain constraints. One or more carrier vehicles, such as a ship or truck, work as a distribution center or service hub for long-distance coverage.

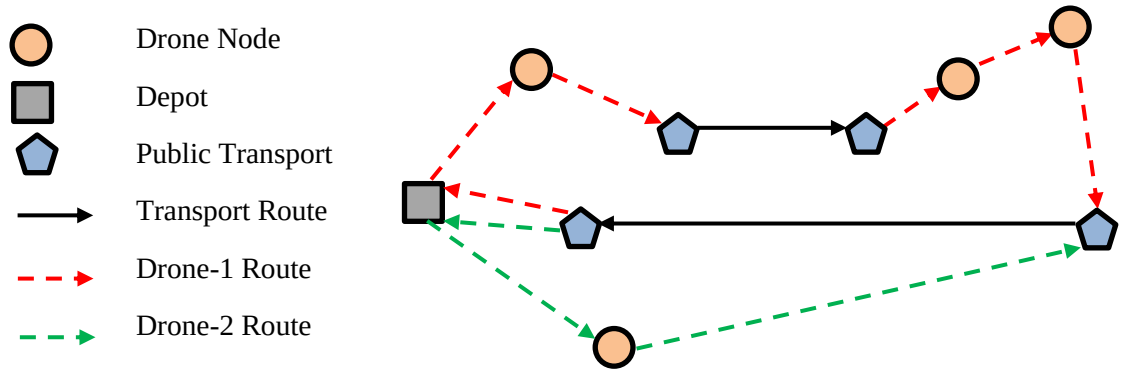

Figure 3: An example of CVRP-D, including two drones with public transport

An example of CVRP-D is shown in Figure 3. Only drones deliver the parcel from the depot to the customer's location. In contrast, the carrier vehicle acts as a service hub and does not participate in end-point delivery. Public transport vehicles are also used as carrier vehicles in some problems [47], [52], [53], [54]. Gómez-Lagos J. et al. [55] implement TSP using parking lots as drone substation. The truck traverses from the depot and stops at a parking lot. This parking lot acts as a substation from where drones deliver parcels to the customer nodes. This scheme bifurcates the final route into two; the first half route for the truck and the remaining half for drones, and helps the vehicle to traverse longer distances and minimize cost.

Other problems considering one truck and multiple drones are TSP-mD, PDSTSP, etc. Tu et al. [56] propose an Adaptive Large Neighbourhood Search (ALNS) and GRASP to solve TSP-mD for 100 customer nodes. In TSP-mD, a truck has *m* homogenous drones to deliver customer parcels. The drone

is launched from one location and later rejoins the truck at another location. For PDSTSP, Dinh Q. et al. [57] propose a Hybrid ACO (HACO) to improve the truck route through local search and dynamic programming by selecting a free vehicle for immediate task assignments. Free drones swap with drones or trucks to reduce waiting time. Mbiadou Saleu R. et al. [58] propose coding and decoding step heuristics based on a split procedure for PDSTSP. Heuristic approaches are popular for multiple vehicle problems with drones [59], [60].

The 2 Echelon VRP with Drone (2E-VRP-D) [61] is a variant of VRP where an intermediate station is designated between the depot and the customer nodes. The truck traverses from the depot to the intermediate station and launches drones to the respective customers. After delivery, drones return to the truck, and the truck returns to the depot. Drones serve one or more customers depending on the payload that can be handled in one trip. The other variants of this problem are 2E-VRP-TW-PD [62] and 2E-VRP-TW [63]. Masmoudi M. et al. [64] propose a VRP-D with multi-package Pay-Load compartments (VRPD-multipackage PL) to maximize the profit of overall service.

Chang Y. and Lee H. [65] propose a heuristic to solve TSP-D where the drone service area is larger than the truck service area. A multi-step strategy is used where the service area is separated into clusters using the K-means clustering technique. Then, the area of these clusters is tried to maximize via Nonlinear Programming (NLP). Salama M. et al. [66] suggest a Launch and Recovery Operation (LARO) for drones which consists of three tasks; (1) assignment of vehicles, (2) routing of the truck and drones, and (3) scheduling vehicles activity at each stop.

A summary of the existing work for one-truck and multiple-drone problems is shown in Table 3, where most solutions involve heuristics and meta-heuristics approaches.

Table 3: Existing techniques for single-vehicle and multiple drones' problems

S. No.	Reference	Year	No. of Vehicles*	Problem	Approach	Objective	Problem Size
1	Wang et al. [52]	2022	1T/MD	Piggyback Transportation Problem	Heuristic	Min time	500
2	Murray C. and Raj R. [44]	2020	1T/MD	FSTSP	MILP + Heuristic	Min time	100
3	Park H. et al. [51]	2022	1T/MD	MDRP	Heuristic	Min path distance	5-40

4	Gómez-Lagos J. et al. [55]	2021	1T/MD	TSP-DP	MILP + GRASP	Min time	10-30
5	Tu A. et al. [56]	2018	1T/MD	TSP-mD	GRASP +ALNS	Min cost	50-100
6	Dinh Q. et al. [57]	2021	1T/MD	PDSTSP	Dynamic Programming + HACO	Min time	23/90
7	Mbiadou Saleu R. et al. [58]	2018	1T/MD	PDSTSP	Dynamic Programming + Heuristic	Min time	10
8	Lei D. et al. [60]	2022	1T/MD	PDSTSP	IVNS	Min time	48-229
9	Masmoudi M. et al. [64]	2022	1T/MD	VRPD-multipackage PL	AMS-SA	Max profit	10
10	Chang Y. and Lee H. [65]	2018	1T/MD	TSP-mD	K-means clustering + Non Linear Programming	Min time	30
Vehicle* - 1T – One Truck, MD - Multiple Drones							

2.3 Multiple Vehicles and Multiple Drones Problems

The optimization problems with multiple vehicles and drones are described in this section e.g., PDSTSP, multiple TSP-D (mTSP-D), and VRP-D. PDSTSP is a variant of the TSP where a fleet of drones and trucks are used to visit a set of nodes. The vehicles perform the delivery independently from the depot to the customer node. There is no synchronization between vehicles. The primary aim is to devise an optimal strategy allowing these vehicles to visit all customer locations while minimizing the distance traveled efficiently. A PDSTSP with three drones and one truck is shown in Figure 4, where trucks and drones deliver independently and follow their paths separately.

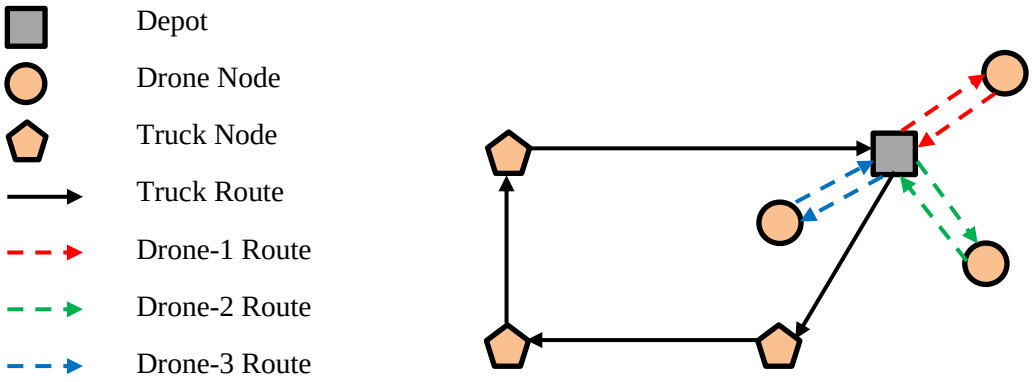

Figure 4: Illustration for PDSTSP with trucks and drones

Ham A. [67] proposes the PDSTSP-DP, where drones and trucks independently deliver parcels from the depot to the designated customer node. In this variant, a drone flies for a pickup from the depot and directly moves on to the next customer for the drop. This problem considers the precedence and re-entrant relationship for multiple trucks, drones, and depots across the service area. The min-cost PDSTSP [68] is a variant of PDSTSP which only focuses on cost minimization. In mTSP-D [69] *m* vehicles form *m* tours and combine them to find the feasible route while satisfying the condition that each node must be visited only once.

The VRP-D arises in many real-world applications, such as package delivery, emergency response, and search and rescue missions. In these applications, drones significantly improve delivery efficiency by reducing travel time, increasing delivery speed, and accessing hard-to-reach locations. The VRP-D variant of the classic VRP involves drones and traditional vehicles, such as trucks or vans. The VRP-D aims to determine the optimal routing of vehicles and drones to service a set of customers while minimizing the distance and maximizing delivery efficiency.

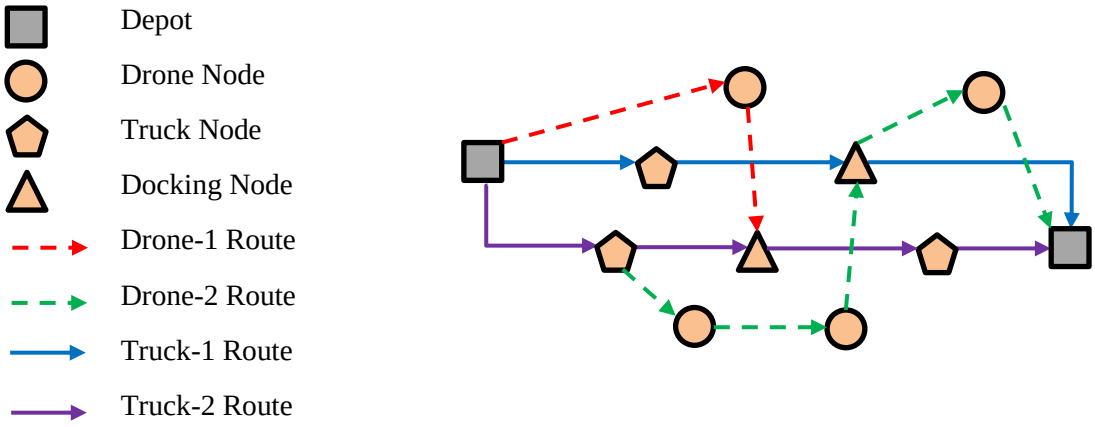

Figure 5: An example of Multi Depot VRP-D, including two drones and two trucks

The difference between CVRP-D and VRP-D is the role of a truck (or large vehicle) in delivery. In CVRP-D, the truck does not participate in end-point delivery and only works as a carrier vehicle for drones. Figure 5 shows an example of this problem with two trucks and two drones. Variants of VRP are Load dependent VRP (LDVRP), Dynamic VRP (DVRP) [70], [71], [72], Multi-Depot VRP (MD-VRP) [73], [74] Two-Echelon VRP (2E-VRP) [75], VRP with Time window (VRP-TW) [76], and Equality-generalized TSP (E-GTSP) [77]. A collaborated Pareto ACO is proposed [78] to solve VRP-TW, where multiple drones synchronize with multiple trucks. The trucks behave as mobile launching

and retrieving sites for drones. Wang et al. [40] uses branch and price for VRP-D, where, after serving customers with one truck, the drone travels back to the docking hub to serve the customers of the next truck. The model compares and validates using Non-dominated Sorting Genetic Algorithm II (NSGA-II). Some variants of VRP-D are presented in [79], [80] using different metaheuristics approaches.

Kitjacharoenchai P. et al. [81] propose multiple TSP-D to minimize the maximum tour length. In this problem, *m*- vehicles visit *n* customers to form *m* tours and return to the depot. The authors propose adaptive insertion and compare the results with the genetic algorithm. On the other hand, Lei D. et al. [82] solve the VRP-D with the Artificial Bee Colony (ABC) and dynamic programming for a small problem size of 15 nodes.

Even after so much work, there are still significant challenges in last-mile delivery [83]. One of the problems is route planning in large service areas for collision-free drone routing. Other routing problems are Piggyback Transportation Problems (PTP) [52], Watchman Routing Problems [84], Same-day Delivery Problems (SDDP) [85], Location Routing Problems (LRP) [86], and Rural Postman Problems [87]. The Refrigerated Routing Problem [88] considers food chain supply within a Time Window (TW). The sustainability of the battery [89], [90] is crucial for optimal energy-efficient routing. Table 4 highlights some multiple truck and drone problems and solution approaches.

Table 4: Existing techniques for multiple vehicles and multiple drone problems

S. No.	Reference	Year	No. of Vehicles*	Problem	Approach	Objective	Problem Size
1	Meng S. et al. [91]	2023	MT/MD	MV-DDP-DP	Heuristics	Min energy Consumption	30
2	Ham A. [67]	2018	MT/MD	PDSTSP	Heuristic	Min time	Up to 100
3	Nguyen M. et al. [68]	2022	MT/MD	PDSTSP	MILP + Heuristic	Min cost	90
4	Das D. et al. [78]	2021	MT/MD	VRP-D-TW	ACO and NSGA-II	Multi-objective	50
5	Wang Z. [40]	2019	MT/MD	VRP-D	Branch & Price	Min cost	Up to 15
6	Huang S. et al. [80]	2022	MT/MD	VRP-D	ACO	Min cost	200
7	Kitjacharoenchai P. et al. [81]	2019	MT/MD	m-TSP-D	Adaptive Insertion Heuristics	Min-max tour length	10

8	Dell'Amico, M. et al. [59]	2020	MT/MD	PDSTSP	MILP, Random restart local search Heuristic	Min time	229
9	Lei D. et al. [82]	2022	MT/MD	VRP-D	ABC + Dynamic programming	Min cost	15
10	Chen X. et al. [85]	2022	MT/MD	SDDP	Deep-Q learning	Max customers	500
11	Montana L. et al. [92]	2022	MT/MD	LRP-D	Heuristics	Min CO_2 emissions.	10-15
12	Mbiadou Saleu R. et al. [93]	2022	MT/MD	PDSTSP	Exact	Min time	50-199
Vehicle* - MT – Multiple Trucks, MD - Multiple Drones, MEV – Multiple Electric Vehicles							

2.4 Drone Delivery Problems (DDPs)

The DDP is a complex logistic challenge that involves drones for transporting goods from one location to another. It is also known as Drone Routing Problem (DRP) [94]. The primary objectives for these problems are minimizing the time, cost, or overall energy consumption to provide faster and more efficient delivery of goods, especially in remote areas or rugged terrain. An example of DDP is shown in Figure 6. DDP deals with the routing of one or many drones. A single drone may be used for monitoring, filming, surveying, and observation (underwater, field, mountain). Multiple drones are required for last-mile deliveries, disaster management, military combat, and extensive service areas. In these problems, drones provide deliveries in a particular area where all vehicles start and return to the depot. The main task is the assignment of drones to the customer nodes to provide service to all customers and reduce the total time of delivery.

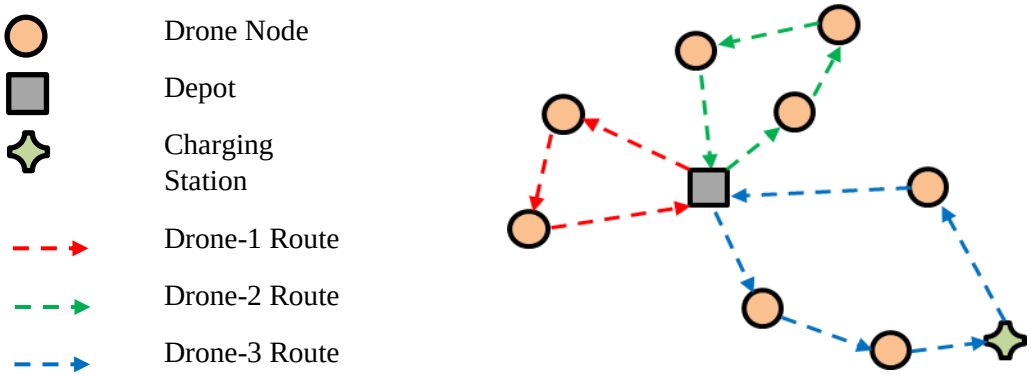

Figure 6: An example of DDP, including three drones with a charging facility

When a drone goes back and forth to make various deliveries from a depot to the customer nodes multiple times, such a problem is known as multi-trip DDP (MT-DDP) [95]. When a drone makes deliveries without receiving a human command, it is called Autonomous Drone Delivery (ADD) [96]. Drone delivery for longer distances requires a network of charging stations and this is called DDP with a Charging Strategy (DDP-CS). The other variant for drone routing is multi-visit DDP (MV-DDP), where a drone visits the customer nodes many times as per demand [91].

Path planning is essential for using drones effectively in the military and civilian domains. In drone-aided routing, the constraint assumption plays a significant role. The wind blowing in the opposite direction adversely affects the drone's speed. Therefore, the flight speed is inversely proportional to the payload and opposite wind speed. Ito S. et al. [97] propose Flight Speed awareness VRP, including Load and Wind (FSVRPLW), to minimize total flight time while considering payload and windspeed constraints. To address the same issue, Chen J. et al. [98] suggest two parallel optimization approaches, Improved Genetic Algorithm (IGA) and Particle Swarm Optimization (PSO)-based Ant Colony Optimization (ACO) to find the optimal path of a drone. In multi-trip problems, drones visit the depot many times. The main drawback of drones is their flying range which constrains them from traveling long distances. DDP-CS is used to resolve this issue. Dorling K. et al. [99] propose Simulated Annealing (SA) and a Mixed Integer Linear Programming (MILP) model to solve two multi-trip VRPs (MTVRP) for a fleet of multirotor drones. The mathematical model verifies that energy consumption is proportional to payload and battery weights.

Arafat M. et al. [100] propose a joint routing and charging strategy for drones to deliver medical supplies. The service area of customers is divided into clusters based on the nearby location of the charging station. Then inter-cluster routing minimizes the number of charging stations. A heuristics approach for flight segmentation deals with the constraints of maximum flight range and safe flight distance. However, the model does not consider weather conditions and flying obstacles. In addition, Kilic K. and Mostarda L. [101] propose two charging station configurations, triangular and square, for optimal charging of drones. The paper presents a boat rescue case study, where flight distance and the number of charging stations are to be minimized. For the same problem, Es Yurek E. et al. [102] incorporate recharging policies for drone batteries, including parameters such as swapping rate,

recharging time, and battery life for results.

DDP-CS is highly effective in making long-distance deliveries. However, the waiting time during drone charging increases the overall costs of operation. Therefore, some studies suggest mobile charging stations rather than fixed charging stations to reduce costs. The use of public transport [54], [53] for drone hopping is an excellent option to travel during long-distance delivery without charging. With its payload, the drone hops and rests on the public transport vehicle traveling on the same route. A drone arrangement called fleet fairies is proposed for data collection in [103], [104] where the goal is to locate the drone service areas for drones and then formulate the routing path using genetic algorithm.

Calamoneri T. et al. [105] propose a model for a rescue operation after an earthquake disaster. Multi-trips with a priorities scheme (a variant of DDP) use a fleet of drones without human control to search for people in need. Shi Y. et al. [106] propose a Multi-Trip Drone Location Routing Problem with Simultaneous Pickup and Drop (MT-DLRP-SPD) for a fleet of drones where drones visit the depot many times depending on pickup and drop demand.

Drones are available in varied sizes and payload capacities. Therefore, some scholars propose incorporating different types of drones into the fleet of vehicles. This variant of DDP is called Heterogenous Fixed Fleet DDP (HFFDDP). For example, Chowdhury S. et al. [107] propose HFFDDP for inspecting a disaster-affected area. In this scheme, several types of drones are incorporated to minimize the cost of operation and overall energy consumption. Most of the existing solutions use heuristic approaches. Only a few researchers propose mathematical models.

Table 5: Existing techniques for drone delivery problems

S. No.	Reference	Year	No. of Vehicles*	Problem	Approach	Objective	Problem size
1	Huang H. et al. [53]	2021	1D	DDP	Dijkstra-based method	Path optimization	--
2	Ghelichi Z. et al. [95]	2021	MD	Multi-trip DLS	Heuristics	Min time	30
3	Ito S. et al. [97]	2022	1D	FSDDPLW	Dynamic Programming	Min time	5-20
4	Chen J. et al. [98]	2017	1D	TSP-D	IGA + PSO + ACO	Path optimization	10-50
5	Dorling K. et al. [99]	2017	MD	MTVRP	MILP + SA	Min time	500
6	Arafat M. et al. [100]	2022	MD	DDP-Recharging	Heuristics	Charging strategy	--

7	Kilic K. and Mostarda L. [101]	2021	MD	DDP-Recharging	Heuristics	Charging strategy	20
8	Hu C. et al. [103]	2021	MD	DDP	GA	Route planning	60
9	Calamoneri T. et al. [105]	2022	MD	Multi trips with Priorities	Heuristics	Min time	--
10	Shi Y. et al. [106]	2022	MD	MT-DLRP-SPD	Pareto ACO and NSGA-II	Bi objective	10-80
11	Chowdhury S. et al. [107]	2021	MD	HFFDDP	Heuristics	Min cost	12 - 40
12	Cheng C. et al. [115]	2020	MD	DDP	Branch and cut	Min cost	35-50
13	Jung H. et al. [116]	2022	MD	DDP	Mathematical Model	Max service	8 island
Vehicle* - 1D – One Drone, MD - Multiple Drones							

Puerto J. et al. [108] propose a crossing postman problem to design the route for drones that visit multiple geographical locations and then move back in a straight-line displacement. Consistent communication is critical for controlling drones. Therefore, many studies present the solution for a flying Ad Hoc network (FANET) [109] to connect a swarm of UAVs efficiently. A stochastic packet forwarding algorithm proposes efficiently transferring data packets [110]. In another approach, Arafat M. and Moh S. [111] propose a Markov decision process (MDP) with Q-learning-based Topology-Aware Routing (QTAR) for route planning. Dubin's vehicle is a mathematical model that only runs forward with a specific curved angle. This car's model helps find the shortest curve to connect two paths. Based on the theory, a windowing surrogate model [112] is proposed for Dubins vehicles to find the optimal path for TSP. Perreault M. and Behdinan K. [113] suggest a driving cycle for optimal drone delivery. A drone's driving cycle refers to the delivery radius covered by it. The aim is to maximize the radii to improve the driving cycle. Gentili M. et al. [114] address the problem of Drone Location and Scheduling (DLS) for serving in emergency scenarios. In this scheme, multiple drones are employed with charging stations to supply medical packages in the emergency area. Table 5 summarizes the single/multiple drone optimization approaches where problem size indicates the number of customer nodes.

3. Current Challenges in Green Vehicle Routing Problems with Drones (GVRP-D)

Conventional fuel-based vehicles are a significant source of carbon emissions contributing to climate

change. The United Nations Development Programme (UNDP) has committed to reducing greenhouse gas emissions by 50% by the year 2030 and is therefore working towards reducing fuel, space heating, and cooling emissions [117]. The United Nations adopted the Sustainable Development Goals (SDGs), commonly known as the Global Goals, in 2015. Goal 7 of the SDGs explicitly promotes affordable and clean energy worldwide. This goal is a universal call to action to encourage the transition towards accessible and environmentally sustainable energy sources [118]. Using EVs instead of conventional fuel-based vehicles can significantly reduce energy consumption, thereby reducing greenhouse gas emissions and helping to meet the UNDP's emissions reduction targets.

One practical approach to achieving this is by adopting electric vehicles (EVs) instead of conventional fuel-based vehicles, as they can significantly reduce energy consumption and greenhouse gas emissions, helping to meet emission reduction targets. According to the International Energy Agency (IEA), the number of EVs globally, excluding two/three-wheelers, is projected to grow from approximately 30 million in 2022 to about 240 million in 2030, achieving an impressive average annual growth rate of approximately 30% [119]. India, too has taken a significant step towards sustainable transportation by announcing its goal to replace/convert all fuel-operated vehicles to electric vehicles by 2030 [120]. This substantial expansion of EVs is expected to play a vital role in India's efforts to curb carbon emissions and promote a sustainable and environmentally friendly transportation system.

Furthermore, the shift towards electric vehicles has given rise to new challenges in optimizing their operational efficiency. The objective here would be to minimize delivery times while considering real-time demand fluctuations, traffic congestion, synchronization constraints, and delivery windows. Replacing conventional vehicles with EVs gives rise to several new (electric) variants of the VRP-D, which involve finding the optimal routes for electric vehicles with drones to visit a set of customer nodes while considering factors such as battery capacity, charging station locations, and charging time. These problems, collectively known as Green Vehicles Routing Problems (GVRP) or Electric Vehicles Routing Problems (EVRP-D), aim to minimize one or more of several parameters, such as fuel consumption, carbon emissions, and other environmental impacts, while ensuring timely and efficient delivery. A key constraint in these problems is the charging of EVs. In the context of drones, these problems are called GVRP with Drones (GVRP-D). The following are some very recent developments

in the GVRP-D domain.

3.1 Green Vehicle Routing Problems with Drones (GVRP-D)

When conventional vehicles are replaced with EVs, the new variant of VRP-D is called Electric Vehicle Routing Problems with Drones (EVRP-D). This involves finding the optimal routes for EVs and drones to visit a set of customer nodes while considering factors such as battery capacity, charging station locations, and charging time. Fan H. et al. [121] suggest a Multi-Depot Open Electric Vehicle and Drones Routing Problem (MD-OEV-DRP) considering factors such as synchronized deliveries with time, vehicle speed, and payload. In this problem, drones can be launched from EVs or Depots. The EVs behave as launching and retrieving platforms for drones. The term "open" implies that multiple depots are available for EVs and drones to initiate delivery routes. This means the delivery operations are not constrained to a single depot or fixed starting point. Furthermore, adding constraints to EVRP-D creates new variants for the problem mentioned below.

3.2 Green Vehicle Routing Problems with Drones & Charging Strategy

A key constraint in these problems is the charging of EVs. A recent application of electric vehicles in combination with drones is the Electric Vehicle Travelling Salesman Problem with Drones (EVTSP-D) [122], wherein an EV with a fixed recharging option is used concomitantly with a drone. The authors propose a solution that uses branch-and-price with constraint programming. The results obtained show a reduction of 10.8% in total average cost. Mara, S. T. W. et al. [123] solve EVRP-D using a Memetic Algorithm (MA). The paper also introduces the recharging policy for EVs where a set of charging stations are planted at launching and/ or retrieving sites of EVs.

3.3 Green Vehicle Routing Problems with Drones & Time Window

Electric vehicles, despite being environmentally friendly, often require more delivery time due to the necessity of vehicle charging. Fixed charging of EVs takes a minimum of 3 to 3.5 hours, which can significantly hinder route optimization for achieving minimum delivery time. On the other hand, opting for partial charging might save time, but it can adversely affect the battery life in the long run. Balancing these factors is crucial for efficient and sustainable logistics operations with electric vehicles. Therefore, the EVRP-D-Time Window (EVTSP-D-TW) is a very challenging problem. Zhu T. et al. [122] extend the EVTSP-D by considering partial charging of the electric vehicle [124], which significantly

minimizes the total operational cost. In some studies, the EVRP-D-TW is also referred to as Green Vehicle Routing Problem with Drones with Time Windows (GVRP-D-TW) [125].

3.4 Multi-objective Green Vehicle Routing Problem with Drones

These Multi-objective Green Vehicles Routing Problems (GVRP-D) [126] aim to optimize several parameters, such as minimum cost, minimum energy consumption, minimum carbon emissions, maximum service area, and others while ensuring timely and efficient delivery. The Electric VRP-D (EVRP-D) is proposed in [127] to reduce energy consumption while completing the delivery task. The authors propose an ACO algorithm with Variable Neighborhood Descent (VND) for multiple EVs and a fleet of homogenous drones.

3.5 Heterogenous Green Vehicle Routing Problem with Drones

Considering various types (configurations) of vehicles in the optimization process facilitates efficient routing with minimized costs. Drones, for instance, are employed for diverse purposes: larger drones are necessary to quickly deliver heavy parcels and ensure timely transport. In comparison, smaller drones are preferred to minimize energy consumption during operations. The objective can be met efficiently by combining both vehicles in the fleet, known as the Heterogenous Green (Electric) Vehicle Routing Problem. The other variant for this problem are Hybrid Electric Vehicle Routing Problem (HEVRP) [128] where hybrid vehicles are used to switch between electric and conventional fuel modes. Table 6 lists some recent approaches to EVs.

Table 6: Existing solutions for GVRP-D

S. No.	Reference	Year	No. of Vehicles*	Problem	Approach	Objective	Problem Size
1	Mara, S. T. W. et al. [123]	2023	MEV/MD	EVRP-D	Memetic Algorithm	Min time	50
2	Kyriakakis N. et al. [127]	2022	MEV/MD	GVRP-D	ACO + VND	Min energy	21-50
3	Fan H. et al. [121]	2022	MEV/MD	MD-OEVRP-D	Genetic Algorithm	Min cost	25-100
4	Zhu T. et al. [122]	2022	1EV/1D	EVTSP-D	Brach-and-Price	Min cost	25
5	Zhu T. et al. [124]	2022	1EV/1D	EVTSPD-P	Heuristics	Min cost	25
Vehicle* - MT – Multiple Trucks, MD - Multiple Drones, MEV – Multiple Electric Vehicles							

The replacement of conventional fuel-operated vehicles with electric vehicles significantly transforms the routing problem by introducing several novel constraints, some of which are detailed as follows.

(a) EVs have limited range capacity compared to fuel-based vehicles. Their performance depends on battery life, weather conditions, road elevation, and driving speed influence their driving distance.

(b) Unlike fuel-based vehicles, which can be refilled at gas stations scattered across the road network, electric vehicles require charging stations. The routing problem needs to incorporate the availability and locations of charging stations to ensure that the vehicle can recharge when needed.

(c) Charging an electric vehicle takes longer than refueling a fuel-based vehicle, increasing the overall travel time.

(d) The routing problem should consider the charging time at each charging station to minimize overall travel time while accommodating the necessary charging stops.

(e) The vehicle's overall weight affects the energy consumption. Therefore, the routing problem may need to consider payload to optimize energy usage.

(f) Extreme weather conditions, such as high or low temperatures, can significantly affect electric vehicles' driving range and energy consumption.

These additional constraints also make EVRP more complex. Furthermore, incorporating EVs with drones makes the problem even more computationally challenging.

The GVRPs are a growing area of research and development with numerous opportunities for innovation and advancement. These routing problems are typically NP-Hard, where finding an optimal solution to the problem is computationally challenging as the problem size increases. Real-world routing problems involve many nodes or vehicles, making it extremely difficult to find an optimal solution within the available time. Also, most of the approaches mentioned in the literature report result in small problem instances. Hence, there is significant scope for developing effective algorithmic approaches for these kinds of problems, which can tackle real-world problem sizes that are typically much larger.

4. Methodology

Routing problems are complex and require careful planning and coordination to ensure efficient and timely delivery. Except for some exceptional cases, these problems are typically NP-hard, which makes routing problems computationally challenging to obtain optimal solutions for even small-size problem

instances in a time-efficient manner. Heuristics and meta-heuristics are commonly used to solve such problems and have proven effective in many cases. Metaheuristics are general-purpose optimization algorithms that apply to many problems, including routing problems. These algorithms are designed to explore a large search space to find a suitable solution quickly and efficiently. Heuristics, on the other hand, are problem-specific algorithms designed to exploit the structure of the problem to find a satisfactory solution.

4.1 Metaheuristics Approaches

Metaheuristics uses iterative search procedures to explore large solution spaces and find optimal or near-optimal solutions. Some well-known metaheuristics are described as follows.

4.1.1 Particle Swarm Optimization (PSO)

The PSO is a nature-inspired yet robust meta-heuristic algorithm for finding the near-optimal solution. It is a computing technique based on the behavior of organisms, for example, a flock of birds or a fish shoal. In PSO, each particle is evaluated by adaptability, position, and velocity. Initially, each particle flies randomly in search space. The basic flow chart of PSO is shown in Figure 7.

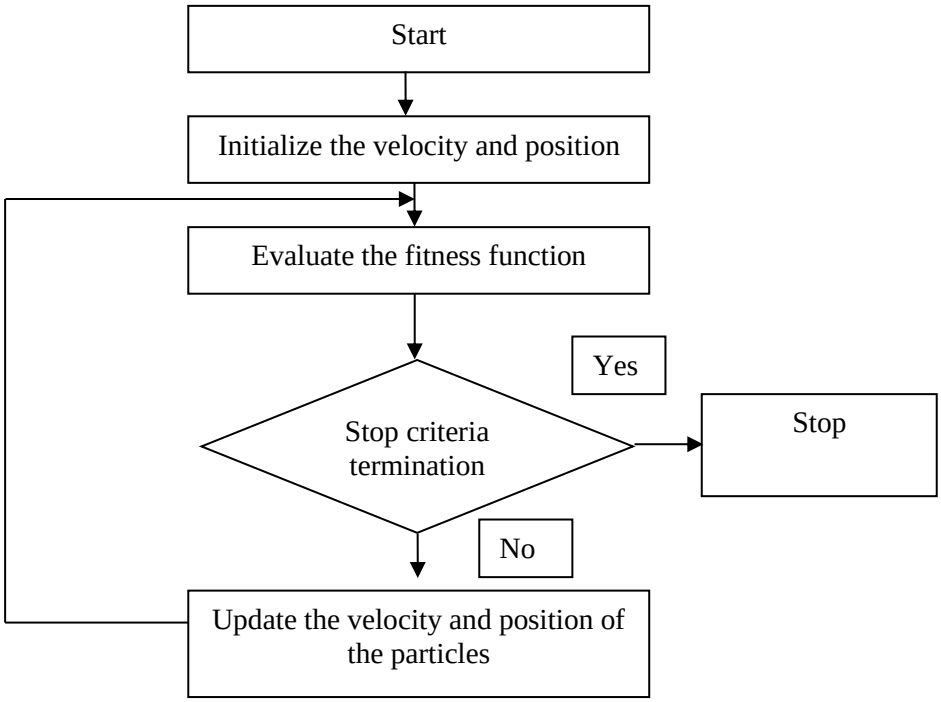

Figure 7: Flow chart for PSO

During movement, each particle tracks its best and neighbor's best positions. The particles continuously change their position in the multi-dimensional search space until the objective is satisfied. The PSO

merges the local and global search (p_{best} and $g_{best)}$ methods. The performance of particles is measured in terms of the fitness function, which is usually proportional to the cost function. It is easy to implement and provides efficient results. The PSO is used for path planning, routing, scheduling, classification, pattern recognition, multi-objective optimization, image segmentation, etc.

4.1.2 Genetic Algorithm (GA)

The genetic algorithm is a metaheuristic that employs evolutionary principles to find optimal or near-optimal solutions. In the context of green vehicle routing problems with drones, genetic algorithms iteratively generate and evolve potential solutions by combining and mutating different routes. This iterative process continues until a satisfactory solution, or a specified stopping criterion, is reached. The algorithm's effectiveness depends on factors such as population size, mutation rate, and selection mechanisms. It is used to resolve both optimization problems; Constrained and Unconstrained. A natural selection process inspires it. The parents are chosen from the current population and produce children for the next generation. The loop iterates itself until the optimal solution. It relies on three operators' mutation, crossover, and selection. It is used for optimization problems, machine learning, routing problems, parametric designing, image processing, parallelization, etc. The basic flowchart for GA is shown in Figure 8.

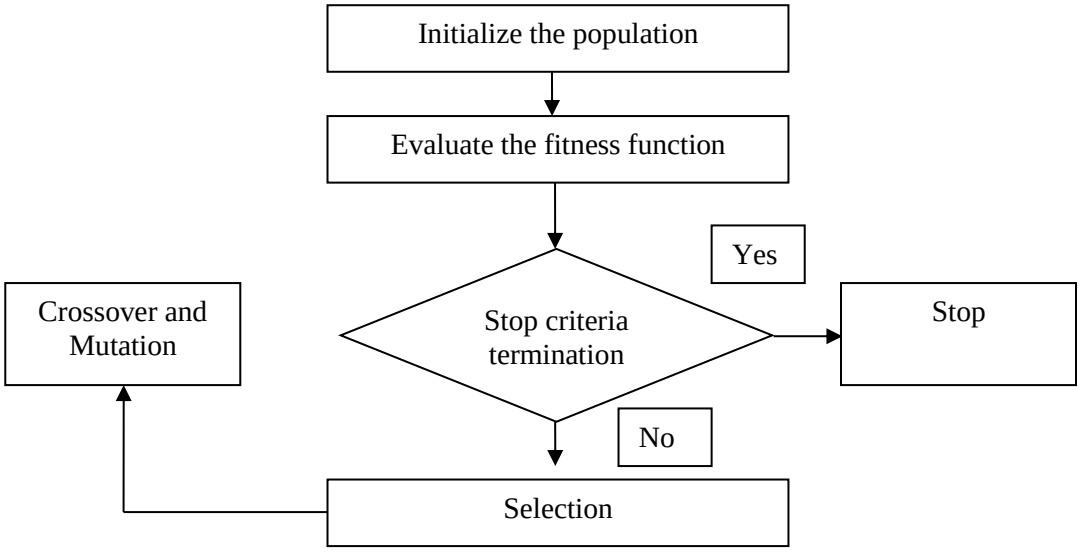

Figure 8: Flow chart for Genetic Algorithm

4.1.3 Ant Colony Optimization (ACO)

The behavior of ants inspires the ACO. The chemical pheromone trails left by ants help them to search

the shortest path for food location. The ACO algorithm solves the problem using the updated pheromone trail to find the direction/path into the search space. The algorithm creates the global ant and its respective fitness value for each iteration. The local ants move towards the better path in case of improved fitness value or continue to search in a random direction.

In the context of green vehicle routing problems with drones, ACO involves the deployment of artificial ants that traverse the problem space, gradually constructing routes while considering factors like distance, energy consumption, and environmental impact. The ACO is used to solve dynamic and stochastic problems such as TSP to find the shortest path. The various applications are classification, prediction, used for scheduling problems, image processing, routing, data mining, etc. The flowchart for the ACO is shown in Figure 9.

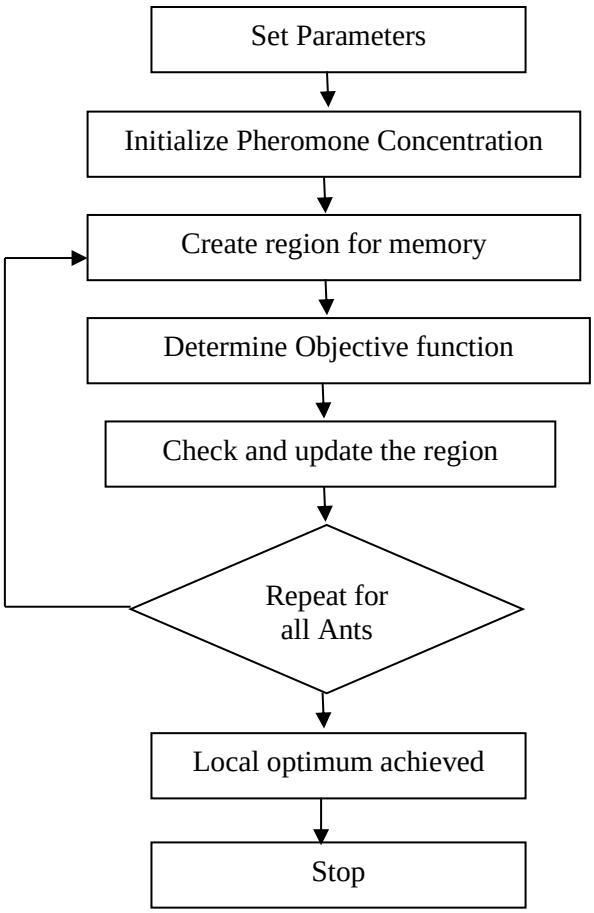

Figure 9: Flow chart for Ant Colony Optimization

4.1.4 Quantum-Inspired Evolutionary Algorithm (QEA)

A quantum-inspired evolutionary algorithm (QEA) [129] is a computational optimization technique

combining principles from quantum computing and evolutionary algorithms. It takes inspiration from quantum mechanics to guide the search process in an evolutionary algorithm, aiming to improve its efficiency and effectiveness in solving complex optimization problems. In a traditional evolutionary algorithm, a population of candidate solutions undergoes reproduction, crossover, and mutation operations to evolve toward better solutions over successive generations. However, the search process in a QEA incorporates quantum-inspired operators to enhance the exploration and exploitation of the search space. Instead of using classical binary strings to represent candidate solutions, QEA employs a quantum-inspired bit representation called a quantum chromosome or individual. The flowchart for the Quantum-Inspired EA is shown in Figure 10.

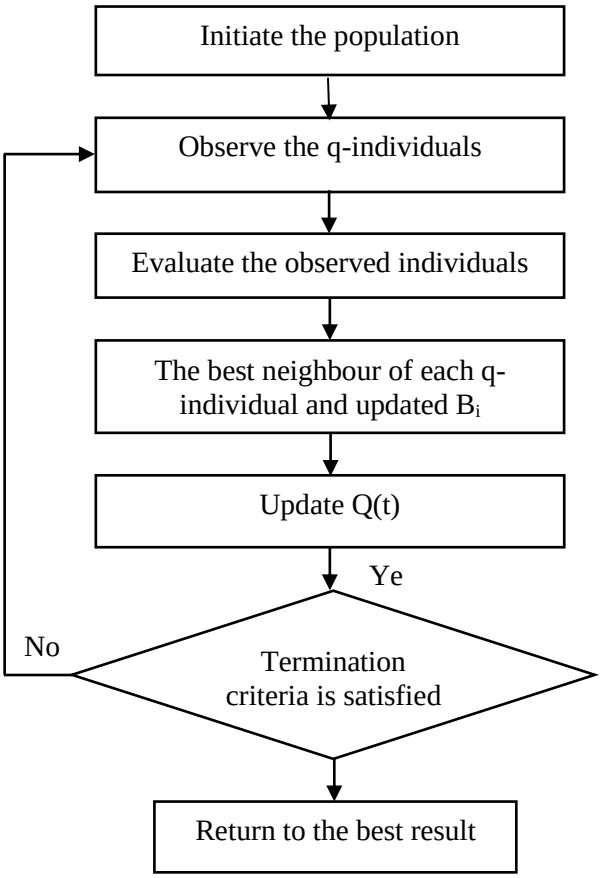

Figure 10: Flow chart for Quantum-Inspired Evolutionary Algorithm

These quantum bits, or qubits, can represent 0 and 1 simultaneously due to the principle of superposition in quantum mechanics. Quantum gate operations mimic the quantum gates used in quantum computing. They manipulate the qubits to perform various operations, such as superposition, entanglement, and measurement. These operations allow for more diverse and efficient search space exploration. Using

quantum-inspired techniques in evolutionary algorithms aims to harness the potential benefits of quantum phenomena, such as superposition and entanglement, to improve search efficiency, overcome local optima, and handle complex optimization problems more effectively.

4.2 Parallel Programming

Harnessing the parallelism inherent in modern multi- and many-core computer architectures can provide a significant performance boost by enabling optimization algorithms to distribute their workload across multiple processing CPU (GPU) cores, thereby enabling faster execution of optimization tasks by simultaneously performing computations on different parts of the problem space. This would also enable the solution of (larger and more complex) problem instances that take too much time and space using sequential approaches.

Parallelism enables multiple search processes to operate simultaneously, providing a more comprehensive and diverse solution for space exploration. It can lead to improved solutions by better avoiding local optima and increasing the chances of finding global optima. The effective use of the parallelism available to perform simultaneous evaluations, gradient calculations and other computations leads to faster convergence. These algorithms are also more scalable since they can dynamically adapt to the underlying computational environment, efficiently utilizing computational resources as available. Increased exploration, faster convergence, and handling the larger problem instances can improve optimization results, achieving better objective values or more desirable tradeoffs. Joblib, multiprocessing, MPI, and CUDA are well-known parallel programming platforms [130].

5. Proposed Work

The literature study of the previous sections throws up several open issues, some of which are proposed to be addressed in the present work.

1. The GVRP-D with EVs and drones for delivery gives rise to several novel constraints that make the problem more challenging. There is good scope for developing more effective models that factor in the vehicle's carrying capacity, charging, availability, and placement within energy windows. The proposed models could be further enhanced to capture multiple conflicting objectives. Therefore, one direction proposed in this work is developing effective models for some GVRP-D variants with real-world scenarios.

2. Results reported by existing algorithmic approaches for GVRP-D variants are limited to small-sized problem instances. Very little work is done on developing effective algorithms better suited for solving large sized, real-world problem instances of GVRP-D variants. Hence, there is good scope for the exploration of fast and effective heuristic and metaheuristic algorithms such as GA, QiEA, and ACO, as mentioned in Section 4 for these problems, intending to obtain better solution quality and/or solving larger, more realistic problem sizes than attempted hitherto. Attempts would also be made to develop practical memetic algorithms that incorporate good heuristic features and result in superior solution quality and faster convergence as compared to existing metaheuristics.
3. Developing practical parallel implementations of the proposed algorithms would enable their application to solve large-sized problems quickly. To this end, suitable parallel programming models such as MPI and OpenMP would be explored as applicable.

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